Logical Correlation-Based Sleep Scheduling for WSNs in Ambient-Assisted Homes

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***Abstract*—This paper proposes a logical correlation-based sleep scheduling mechanism named LCSSM to implement energy-efficient wireless sensor networks (WSNs) in ambient assisted homes (AAHs). LCSSM analyzes sensory data generated by different human behaviors to detect the logical correlations between sensor nodes in an AAH. By utilizing the particular logical correlations of an AAH to predict its usage status, LCSSM deactivates sensor nodes accordingly to save energy when they are not expected to sense any valuable event. Evaluation results based on real life-logs have validated that LCSSM not only reduces the energy consumption of WSNs significantly, but also retains their quality of sensing successfully, e.g., with a moderate assumption on the duty cycling ratio and hardware configuration of sensor nodes, LCSSM successfully senses 98.7% valuable events with an average of 37.0% usual energy consumption, and extends the life time of WSNs by 63.4%.**

***Keywords*—sleep scheduling, energy conservation, wireless sensor networks, ambient assisted home.**

I. Introduction

Recent improvements in medical care allow people to live longer and healthier compared with the previous generations. It has been estimated that 21.8% of the world population will be over the age of 60 by the year 2050 [1, 2]. Japan, one of the most representative countries, is estimated to have 36.8 million people over the age of 65 in 2030 [3]. In addition, more and more elders tend to live alone in their own homes so as not to be a burden on family or friends, and not having to adjust to the needs of others [3]. However, due to the lack of caregiver, these single elders are easier to suffer from health problems and accidents such as diabetes, senile dementia, decubitus ulcers, fall, or even lonely death [2, 3]. Therefore, both governments and society are expecting innovative healthcare services for them that are both high-quality and cost-effective.

At the same time, advances in wireless networking, sensing, and ubiquitous computing areas converge to an exciting engineering research field named "Internet of Things (IoT)" [4, 5]. Briefly speaking, IoT envisions a near future in which the objects of everyday life will be equipped with microcontrollers, communication transceivers, and network protocol stacks that enable them to communicate with each other and become an integral part of the Internet. Therefore, ambient assisted home (AAH), a kind of IoT applications that aims at evaluating the wellness of elders by remote sensing, is assumed to be one of the most promising solutions to the aforementioned issue in the aging society [6–11]. As depicted in Fig. 1, heterogeneous smart sensors are deployed in an AAH to sense the daily behaviors (e.g., sleeping, showering and toileting), the resource usage (e.g., water, electricity, and gas), and the living environment (e.g., temperature and humidity) of a single elder. Sensory data are analyzed by healthcare professionals or expert systems (H&E) to evaluate her/his physical and mental conditions.

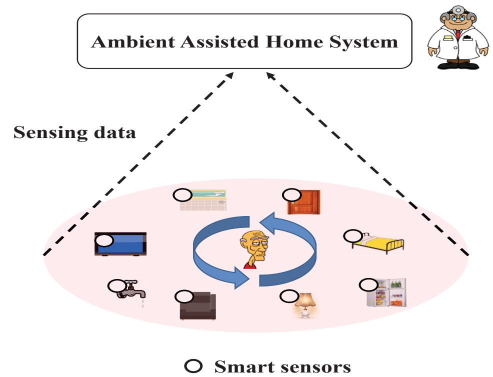

Fig. 1: Ambient assisted living home.

Wireless sensor nodes (SNs) are small devices that integrate computing (processing units), wireless communication (radios), and sensing (sensors) abilities. SNs connected by wireless media form wireless sensor networks (WSNs) to sense the physical environment. WSNs are suitable for implementing AAHs, since they remove the requirement of deploying wired devices and are easy to be implemented in existing home environments. Besides, small and low-cost SNs can be placed in furniture, appliances, or movable objects where it was impractical to implement sensors before [7]. However, due to the limited battery capacity, SNs have short lifetime and require frequent battery replacement, e.g., six popular SN platforms listed by Carrano et al. [12] deplete their batteries in few days of continuous activity. This drawback is preventing WSNs-based AAHs from being accepted by industries as a practical solution. Unfortunately, to our best knowledge, little existing work except [7, 8] considered the energy issue of WSNs in the background of AAH. As explained in Sect. II, these existing mechanisms do not well satisfy the requirements of AAH applications.

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(a) Duty cycling.

(b) Sleep scheduling.

(c) Sleep scheduling & Duty cycling.

Fig. 2: Energy conservation mechanisms for sensor nodes in WSNs.

Clinical observations show that human functions follow periodical variations regulated by internal biological rhythms [13] and their daily behaviors also periodically fluctuate according to imperative schedules such as sleep, wake-up, meals, and leisure. Therefore, an AAH is not always used to its full extent, e.g., when the resident is sleeping, appliances like TV and microwave are not likely to be used. According to the observation, this paper proposes a mechanism that analyzes the sensory data generated by different human behaviors to detect the logical correlations between SNs in an AAH. By using the particular logical correlations of an AAH to predict its usage status, the proposed mechanism activates/deactivates SNs accordingly to save their energy. The three main contributions of this paper are: (1) The concept of logical correlation is introduced to measure the relationships between SNs in AAHs. (2) This is the first sleep scheduling mechanism for WSNs in AAHs that is adaptive to the behavioral traits of different residents, to our best knowledge; and (3) Extensive evaluation results based on real life-logs have validated that the proposed mechanism not only reduces the energy consumption of WSNs significantly, but also retains their quality of sensing successfully.

Following the background and literature review in Sect. II, Sect. III explains the system model of AAH. The concept and analysis of logical correlation are presented in Sect. IV. Section V introduces the proposed sleep scheduling mechanism, and its evaluation results are shown in Sect. VI. Finally, conclusions are drawn and future work is discussed in the last section.

II. Background Knowledge and Related Work

There is a great deal of related work due to the importance of energy-efficient WSNs. This section introduces them briefly, especially from their use in the background of AAH applications. Excluding the strategy depending on renewable energy source like solar energy that is not feasible in the indoor environment, the related work can be roughly divided into two categories: duty cycling on the radio of SN, and sleep scheduling on the sensing activity of SN.

A. Duty Cycling on the Radio of SN

Duty cycling is a fundamental strategy to achieve energy-efficient WSNs. It turns an SN's radio on and off to avoid having the radio of waiting in vain for a frame. Polastre et al. proposed a carrier sense media access protocol named B-MAC [14], and it employs an adaptive preamble sampling scheme to reduce the duty cycle of radio. Ye et al. introduced a contention-based media access protocol named S-MAC [15], in which SNs form loosely virtual clusters to auto-synchronize on sleep schedules. Their proposal not only sets the radio to sleep during the transmission of other nodes, but also applies message passing to reduce the contention latency. In general, schedule-based MAC protocols are more energy-efficient than the contention-based ones, while they require a central controller to manage the scheduling process. Therefore, Le et al. proposed a hybrid MAC protocol [16] that integrates the advantages of both approaches. The performance evaluations have validated that their hybrid protocol not only consumes less energy than S-MAC, but also achieves a lower transmission delay. Regarding the duty cycling mechanism for WSNs in AAHs, Pensas et al. used the location information of resident to schedule SNs [7], i.e., using a high duty cycle for SNs in the room where the resident is in to ensure the quality of sensing, while reducing the duty cycle for SNs in other rooms to save energy. As depicted in Fig. 2(a), these duty cycling mechanisms adhere to the energy efficiency of radio without considering the energy consumed by other parts of the SN like its processing unit (CPU) and sensor.

B. Sleep Scheduling on the Sensing Activity of SN

As surveyed by Carrano et al. [12], the radio of popular SN platforms usually consumes 2 times of energy in compare with their CPU, and this is why duty cycling has attracted most attention of researchers. However, if we further consider an SN that is already with certain duty cycling mechanism, its CPU may become the dominant energy consumer, e.g., with a conservative duty cycling ratio of 10%, the CPU in popular SN platforms conversely consumes 5 times of energy in compare with the duty-cycled radio. In addition, with the diversification of WSN applications, researchers have realized that various kinds of sensors, e.g., pressure, humidity, proximity, gas and flow control sensors, may consume tens of times more energy than the radio of SNs [17–19]. It reveals, by deactivating CPU and sensor, an SN can reduce its energy consumption to $< 67\%$ (with a common radio and an energy-saving sensor), $< 17\%$ (with a 10% duty-cycled radio and an energy-saving sensor), or $< 10\%$ (with a low duty-cycled radio or an energy-hungry sensor). Therefore, more and more researchers tend to reduce the energy consumption of SNs by deactivating their sensing activities [8, 20–24]. This kind of sleep scheduling

TABLE I: The limitations of related work in the background of ambient assisted homes.

Strategy	Papers	Limitations
Duty Cycling	[7, 14-16]	Adhering to the energy efficiency of radio without considering the energy consumed by other parts of the SN like CPU and sensor.
Sleep Scheduling	[8]	Depending on a network administrator to determine the sleep scheduling policy manually.
	[20-23]	Assuming that a high density of homogeneous SNs exists in the target area and the correlation between SNs depends on their geographical positions.
	[24]	Failing to retain the energy efficiency of WSNs when the correlation between SNs seems to fluctuate according to different human behaviors in a home.

mechanisms can be used as a replacement or a complement to the duty cycling mechanism as shown in Figs. 2(b) and (c).

Wood et al. presented a WSNs-based AAH named "Alarm-net" [8]. It enables a control flow to activate/deactivate SNs, aiming at implementing energy-efficient WSNs. However, their proposal depends on a network administrator to determine the sleep scheduling policy manually. Akyildiz et al. exploited the spatiotemporal correlation of sensory data to implement energy-efficient WSNs [20]. Their mechanism partitions SNs into clusters so that SNs in the same cluster have similar surveillance time series. In every cluster, a representative SN is kept active to sense the environment while others are turned off to save energy. A similar energy-efficient data collection framework for WSNs was proposed by Liu et al. [21]. Compared with the mechanism described in [20], this framework enables SNs in the same cluster to act as the representative node in turn so that they can share the workload and extra energy consumption. Villas et al. proposed a mechanism that divides the target area into geographically nearby cells according to the spatial correlation of sensory data [22]. Again, a representative SN is selected to sense the cell while others are turned off. Regarding the selection of representative SN, this mechanism not only considers the workload of SNs but also takes their remaining battery energy into account. In addition, a runtime-efficient heuristic algorithm was proposed by Karasabun et al. [23] to select the representative SN of a cluster. However, this work does not explain how to obtain the correlation between SNs. All the previous four mechanisms assume that a high density of homogeneous SNs exists in the target area and geographically nearby SNs are likely to produce redundant sensory data. This assumption works well for the large-scale WSNs that monitor outdoor environment conditions like temperature and air quality, but fails to satisfy the requirement of AAH applications since nearby SNs in a home may have totally different functions.

A very recent mechanism called energy-efficient clustering method using random update (EECRU) [24] is the most similar to our study. EECRU uses the average entropy of sensory data to measure the correlation between SNs without considering their geographical positions, and groups SNs into clusters accordingly. Similar to the previous mechanisms, a representative SN is selected to sense the environment while other SNs in the same cluster are deactivated to save energy. A dynamic cluster update method and a rotation scheme to select the representative SN were also introduced. However, as illustrated in Sect. VI, EECRU fails to retain the energy efficiency of WSNs in the background of AAH. This is because the correlation between SNs in a home seems to fluctuate according to different human behaviors frequently. Without the ability of data preprocessing and filtering, EECRU cannot discover a steady correlation between SNs and thus cannot cluster SNs efficiently. Table I summarizes these related mechanisms and their limitations in the background of AAH.

III. System Model

This paper assumes that heterogeneous SNs spread in an AAH to monitor a single elderly resident. Without loss of generality, S_{xxx} is used to represent an SN where the subscript indicates the target that it monitors, e.g., S_{bed} represents an SN monitors the status of a bed in the home. Since this paper focuses on the sleep scheduling of sensing activity, the discussion of duty cycling mechanism is beyond its scope. However, our proposal can integrate existing duty-cycling mechanisms as shown in Fig. 2(c). There are two modes for an SN:

(1) **Active mode:** The SN performs sensing activity in this mode. Both its sensor and CPU are activated to sense events and process sensory data. Its radio is also activated periodically according to a predetermined duty cycle to transmit sensory data and receive sleep scheduling messages. This mode is energy consuming.

(2) **Sleep mode:** The SN does not perform any sensing, processing, or transmission activity in this mode. Only its radio is activated periodically according to a predetermined duty cycle, so as to receive sleep scheduling messages. This mode is energy efficient, but fails to sense any event.

A home gateway (HG) in the AAH, that can communicate with SNs in a single-hop fashion[1], acts as a communication bridge between WSNs and back-haul networks. It receives sensory data from WSNs, and relay them to "cloud" (data center) by cellular or broadband networks. These sensory data are analyzed by H&E to evaluate the wellness of elder resident. Although some deployment environments may enable the use of main-power, we do not require it except for the HG, so

[1]This is not a mandatory assumption. Since the proposed mechanism only schedules the sensing activities of SNs without concerning their transceivers, it can smoothly integrate any transceiver mechanism that ensures the multi-hop communications between SNs and HG. We make this assumption to focus on the sleep scheduling mechanism, without involving WSNs routing protocol that is a large topic by itself.

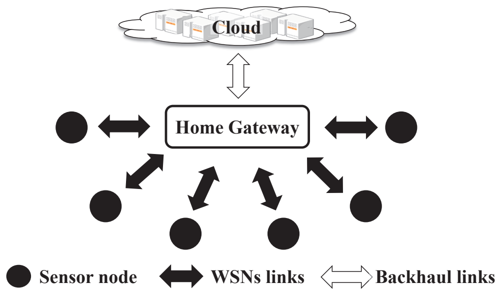


Fig. 3: System model.

as to support ad hoc retrofitting of existing home structures. Therefore, benefitted from its greater capabilities of communication, computation and power-supply, HG is supposed to perform the major aspects of system operations like sensory data analyses and the sleep scheduling of WSNs.[2] Figure 3 indicates the proposed system model.

An active SN senses its corresponding events that occur in an AAH, e.g., an SN in the toilet (S_{toilet}) senses whether the toilet is in use. However, not every sensed event is valuable for H&E to evaluate the wellness of elders. Assume that one aim of an AAH is to judge whether the monitored elder suffers from diarrhea by observing her/his frequency of using toilet. When S_{toilet} senses an event of using toilet, it should report it to H&E to facilitate their work. Thus, this kind of events is named "valuable events" (VEs) in this paper. Conversely, when S_{toilet} only senses an event of idle toilet, there is no need for the SN to report this event since it provides little information to H&E. As a result, this kind of events is named "negligible events" (NEs). Table II lists some examples of VEs for different SNs in an AAH. It should be noted that the definition of VEs depends on the needs of H&E. Different VEs can be defined for the same SN in different AAHs, e.g., according to the health conditions of different elders.

It is clear that there is a tradeoff between the energy consumption of SNs and their quality of sensing, i.e., keeping SNs asleep saves energy but increases the risk of missing VEs, and vice versa. Figure 4 depicts this tradeoff pictorially. It is clear that an ideal sleep scheduling mechanism should activate an SN only when its VEs occur, i.e., every SN can sense all of its VEs to ensure a perfect quality of sensing with the minimum energy consumption. Therefore, this paper proposes a concept of logical correlation between SNs to predict the occurrence of their VEs. A corresponding mechanism is designed to schedule the sensing activity of SNs and reduce their energy consumption.

IV. Logical Correlation between SNs

The theoretical model of logical correlation between SNs is presented in this section. Specifically, Sect. IV-A introduces the concept of logical correlation, and Sect. IV-B discusses the measurement of logical correlation. Without loss of generality, VEs listed in Table II are used in this section to clarify the following definitions.

[2]The HG is a sink node in the home WSNs. Depending on the capability of HG, these system operations can either be performed by itself or by the powerful "cloud". We do not distinguish these two cases and assume a powerful HG in this paper.

TABLE II: VEs in an AAH.

Sensor node	Type	Valuable events
S_{bed}	pressure	The resident is sleeping in the bed.
$S_{TV-chair}$	pressure	The resident is sitting on the chair.
S_{TV}	electric	The TV is power on.
S_{fridge}	electric	The fridge is power on.
S_{shower}	flush	The resident is showering.
S_{toilet}	flush	The resident is using toilet.

A. *Concept of Logical Correlation*

In this paper, logical correlation is defined to measure the strength of relationship between a pair of SNs, i.e., the likelihood of their VE co-occurrence. There are three kinds of logical correlations:

Positive correlation: VEs for the pair of SNs are likely to co-occur at the same time, e.g., the correlation between $S_{TV-chair}$ and S_{TV}, since the resident is used to sitting on the chair to watch TV.

Negative correlation: VEs for the pair of SNs are unlikely to co-occur at the same time, e.g., the correlation between S_{bed} and $S_{TV-chair}$, since the resident is unlikely to sleep in the bed and sit on the chair simultaneously.

Lack of correlation: The occurrence of VEs for the pair of SNs is not related, e.g., the correlation between S_{bed} and S_{fridge}, since whether the resident is sleeping in bed depends little on the power state of fridge.

The logical correlations between SNs can be represented by a graph where vertices correspond to SNs and edges correspond to their pairwise correlations. It is called logical correlation graph (LCG) in this paper, and Fig. 5(a) gives an example. It is obvious that the logical correlations between SNs in an AAH highly depend on the behavioral traits of its resident, e.g., an environmentalist who goes to shower with TV off to save electricity and a careless resident who goes to shower with TV on cause different correlations between S_{TV} and S_{shower}.

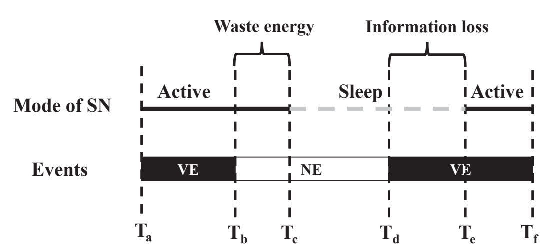


Fig. 4: The tradeoff in sleep scheduling.

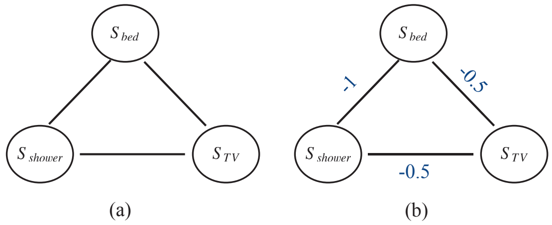


Fig. 5: Logical correlation graph.

	S_{bed}	S_{shower}	S_{TV}
slot 1	1	0	0
slot 2	1	0	1
slot 3	0	1	0
slot 4	0	1	1

(a)

C_{shower}	C_{TV}
0	0
0	1
1	0
1	1

(b)

C_{shower}	C_{TV}
0	1
1	0
1	1

(c)

C_{shower}	C_{TV}
$-\sqrt{2}$	$\frac{\sqrt{2}}{2}$
$\frac{\sqrt{2}}{2}$	$-\sqrt{2}$
$\frac{\sqrt{2}}{2}$	$\frac{\sqrt{2}}{2}$

(d)

Fig. 6: Measuring logical correlations in AAHs.

B. Measurement of Logical Correlation

Since different behavioral traits of residents generate different logical correlations between SNs, an accurate measurement of logical correlation is essential to produce customized sleep scheduling policies for WSNs in different AAHs. Without loss of generality, we assume that there exist sensory data in an AAH across a period of T_{sense}.

1) Preprocessing of Sensory Data: Heterogeneous SNs in the AAH generate sensory data with disparate scales/units, e.g., pressure, temperature, and humidity. The concept of VEs described in Sect. III is used to transform these data into a unified framework for future analysis. First, the period T_{sense} is discretized into time slots with a length of Δt like tens of seconds or several minutes. As a result, the total number of time slots is

$$N_{ts} = \frac{T_{sense}}{\Delta t}. \tag{1}$$

Then, let x^i_{SN} indicate whether an SN senses its VEs in the i-th time slot,

$$x^i_{SN} = \begin{cases} 1 & \text{Senses at least one VE in the } i\text{-th time slot,} \\ 0 & \text{Only senses NEs in the } i\text{-th time slot,} \end{cases} \tag{2}$$

where the subscript represents the name of the SN. For example, $x^i_{S_{TV}} = 1$ means that the TV is power on in the i-th time slot according to Table II. Consequently, heterogeneous sensory data are transformed into a matrix composed of x^i_{SN}, where the row index indicates the sequence number of time slots and the column index indicates the name of SNs. Figure 6(a) shows an example of the transformed matrix that includes data collected from three SNs in four time slots. Each row of this matrix actually captures a snapshot of the AAH, e.g., in time slot 1, the resident was sleeping in the bed, the TV was power off, and the shower was not being used.

2) Logical Correlation Coefficient: Based on the transformed matrix, logical correlation coefficient (LCC) that is a real number ranges in [-1,1] is used to measure the strength of logical correlation between a pair of SNs. Without loss of generality, the LCC between S_{shower} and S_{TV} shown in Fig. 6(a) is considered. First, their corresponding columns in the matrix are cloned into two vectors, C_{shower} and C_{TV}, as shown in Fig. 6(b). c^i_{shower} and c^i_{TV} are used to represent their i-th elements.

Filter: Eliminate c^i_{shower} and c^i_{TV}, if they are both zero. Since this indicates only NEs were sensed in the i-th slot, they are unrelated to the logical correlation between S_{shower} and S_{TV} that only concerns the co-occurrence of their VEs. Figure 6(c) shows the resulting C_{shower} and C_{TV}. There are four special cases for a pair of filtered vectors. Without loss of generality, C_A and C_B are used to represent them.

(1) Both C_A and C_B are constant on one:

It indicates their corresponding SNs, S_A and S_B, always sense VEs simultaneously. Consequently, their LCC is given by

$$LCC(S_A, S_B) = 1. \tag{3}$$

(2) C_A is constant on one, but C_B is constant on zero:

It indicates S_A always senses its VEs when S_B senses its NEs. As a result, their LCC is given by

$$LCC(S_A, S_B) = -1. \tag{4}$$

(3) Both C_A and C_B are empty:

It indicates both SNs only sense NEs in the period T_{sense}. Consequently, there is no way to induce their logical correlation because VE never occurs,

$$LCC(S_A, S_B) = 0. \tag{5}$$

(4) C_A is constant, but C_B is not:

Since a constant vector is independent of random vectors, there is no relationship between the co-occurrence of two SNs' VEs,

$$LCC(S_A, S_B) = 0. \tag{6}$$

It should be noted that the correlation coefficient of constant vector is not defined in the theory of statistics. Therefore, previous special definitions are appropriate in the background of this paper, but may not apply to every other situation.

Normalization: Since C_{shower} and C_{TV} shown in Fig. 6(c) are not constant or empty, the calculation process continues. For any vector C, the average value $E(C)$ and the standard deviation $SD(C)$ of its elements are given by

$$E(C) = \frac{\sum_{i=1}^{K} c^i}{K}, \tag{7}$$

$$SD(C) = \sqrt{\frac{\sum_{i=1}^{K}(c^i - E(C))^2}{K}} \ , \qquad (8)$$

where c^i represents the i-th element of C and K is the dimension of C. Therefore, C can be normalized by

$$c^i = \frac{c^i - E(C)}{SD(C)} \qquad i = 1, 2, ...K \ . \qquad (9)$$

Applying Eqs. (7), (8), and (9) to C_{shower} and C_{TV} results in the vectors shown in Fig. 6(d).

Calculation: The LCC between S_{shower} and S_{TV} is calculated by the normalized scalar product of C_{shower} and C_{TV},

$$LCC(S_{shower}, S_{TV}) = \frac{C_{shower} \cdot C_{TV}}{K} = -0.5 \ . \qquad (10)$$

By using LCCs to weight edges, the resulting LCG quantitatively reveals the latent logical correlations between SNs in the AAH. Figure 5(b) illustrates the LCG generated from Fig. 6(a). Finally, since the calculation of LCC between a pair of SNs only involves linear operations on two N_{ts}-dimensional vectors, its computational complexity is $O(N_{ts})$. When there are N SNs in the AAH, the total complexity of computing their LCG is $O(N_{ts} * N^2)$. Consequently, the length of time slots Δt presents a tradeoff between the accuracy of LCG and its computational overhead. A small Δt refines the granularity of matrices in Fig. 6 and improves the accuracy of logical correlations, while it also increases the overhead of computing logical correlations since a larger N_{ts} is introduced according to Eq. (1).

V. Logical Correlation-based Sleep Scheduling

As described in the previous section, a strong negative correlation between two SNs, S_i and S_j, reveals an inverse relationship on the co-occurrence of their VEs, i.e., if S_i senses its VEs, S_j is likely to sense its NEs simultaneously, and vice versa. Therefore, when either S_i or S_j senses its VEs, the other SN can be deactivated safely to save energy since it is expected to sense NEs only. Motivated by this observation, a **l**ogical **c**orrelation-based **s**leep **s**cheduling **m**echanism called LCSSM is devised to implement energy-efficient WSNs in AAHs.

A. Framework of LCSSM

At the beginning of LCSSM, HG collects sensory data from WSNs to generate an LCG according to the algorithm described in Sect. IV-B. This is the training phase of LCSSM and can be finished off-line. After that, HG runs LCSSM to schedule SNs in the AAH. Initially, all SNs are active and HG receives sensory data from SNs as normal. However, for each S_j that is sensing its VEs, HG deactivates S_i if it is sensing NEs and has a strong negative correlation with S_j, i.e. $LCC(S_j, S_i) \leq \alpha_i$. Here, α_i is a threshold of negative correlation to deactivate S_i, and ranges in [-1,0). It was determined for every SN in the training phase by a sub-routine discussed in Sect. V-B. A sleep S_i is re-activated when all nodes S_k that satisfy $LCC(S_k, S_i) \leq \alpha_i$ begin to sense their NEs, since it indicates S_i may sense its VEs from now on. The pseudo-codes of LCSSM are presented in Table Algorithm 1.

Algorithm 1: LCSSM

Require: D_{train}, Δt;
  D_{train}: training sensory data;
  Δt: the length of time slot to generate LCG;

/***************** Training phase *******************/
1 Generate LCG with D_{train} and Δt; // Sect. IV-B
2 **foreach** SN, S_i, in the AAH
3   α_i = TOS(S_i, LCG, D_{train}); // Sect. V-B

/***************** Running phase *******************/
4 **while** (receive sensory data from SNs)
5   **foreach** active SN, S_j, that is sensing its VEs
6   **foreach** S_i other than S_j
7   **if** (S_i is active and sensing its NEs)
8   **if** ($LCC(S_j, S_i) \leq \alpha_i$)
9   Deactivate S_i to save energy;
10   **if** (S_i is sleeping)
11   **if** ($LCC(S_j, S_i) \leq \alpha_i$)
12   Mark S_i to keep sleeping;
13   Re-activate sleep SNs that are not marked in the line 12;

B. Threshold Optimization

The final remaining issue of LCSSM is how to determine the threshold of negative correlation to deactivate each SN. A larger threshold α_i deactivates S_i more aggressively to save energy, but induces a higher risk of missing VEs that degrades the quality of sensing, and vice versa. Formally, VE hit ratio is defined to indicate the quality of sensing for an SN:

Definition 1: VE hit ratio (VHR): The percentage of occurred VEs that have been sensed by the SN.

The aim of LCSSM is to save energy of SNs without compromising their quality of sensing too much. Without loss of generality, the threshold α_i to deactivate S_i is considered in the following descriptions. Let $E(\alpha_i)$ and $V(\alpha_i)$ denote the energy consumption and VHR of S_i in any time interval T. The optimization of α_i, that aims at minimizing the energy consumption of S_i with a constraint of its sensing quality, is formalized as:

P.1:

$$\begin{aligned} &\text{Objective:} && \text{Min. } E(\alpha_i) \ , \\ &\text{Subject to:} && V(\alpha_i) \geq V_{i-cons} \ , \\ & && 0 > \alpha_i \geq -1 \ , \end{aligned}$$

where V_{i-cons} is a constraint of S_i's expected VHR. It can be defined by H&E to declare their tolerance of information loss, e.g., a constraint of 0.9 means a 10% loss of VEs for S_i is tolerable.

Define T_{j-ve} as a set of sub-time intervals in T, during which VEs for S_j occur. According to LCSSM, S_i is deactivated during T_{j-ve}, if $LCC(S_j, S_i) \leq \alpha_i$. $K(\alpha_i)$ represents the set of all SNs that satisfy this inequality,

$$K(\alpha_i) = \{S_j | LCC(S_j, S_i) \leq \alpha_i\} \ . \qquad (11)$$

Since LCSSM deactivates S_i and keeps it asleep if any SN in $K(\alpha_i)$ senses its VEs, the set of sub-time intervals during

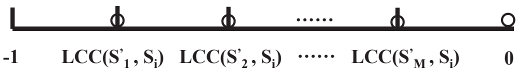


Fig. 7: Intervals divided by M negative correlation coefficients, i.e. $[-1, LCC(S_1^{'}, S_i))$, $\cdots$, $[LCC(S_M^{'}, S_i), 0)$.

which S_i is asleep is

$$T_{sleep}(\alpha_i) = \bigcup_{j \in K(\alpha_i)} T_{j-ve} \ . \tag{12}$$

Conversely, the set of sub-time intervals during which S_i is active is

$$T_{active}(\alpha_i) = T - T_{sleep}(\alpha_i) \ . \tag{13}$$

Therefore, the energy consumed by S_i is given by

$$E(\alpha_i) = P_{i-active} \times |T_{active}(\alpha_i)| + P_{i-sleep} \times |T_{sleep}(\alpha_i)| \ , \tag{14}$$

where $P_{i-active}$ and $P_{i-sleep}$ represent the electric powers of S_i in active and sleep modes, and $|\cdot|$ is the sum of sub-time intervals in a set, e.g., $|\{[5:00, 5:30], [7:00, 7:30]\}| = (5:30 - 5:00) + (7:30 - 7:00) = 60$ mins. In addition, since a sleep SN fails to sense any VE, the VHR of S_i is given by

$$V(\alpha_i) = \frac{|T_{i-ve} \bigcap T_{active}(\alpha_i)|}{|T_{i-ve}|} \ , \tag{15}$$

where T_{i-ve} is the set of sub-time intervals in T during which VEs for S_i occur.

Theorem 1: $E(\alpha_i)$ and $V(\alpha_i)$ are monotone non-increasing in α_i.

Proof: Assume that there are two thresholds α and $\alpha^{'}$ for S_i, and $\alpha \geq \alpha^{'}$. Their corresponding $K(\alpha)$ and $K(\alpha^{'})$ are: $K(\alpha) = \{S_j | LCC(S_j, S_i) \leq \alpha\}$ and $K(\alpha^{'}) = \{S_j | LCC(S_j, S_i) \leq \alpha^{'}\}$. Since $\alpha \geq \alpha^{'}$, $K(\alpha^{'}) \subseteq K(\alpha)$. By applying Eqs. (12) and (13), $T_{sleep}(\alpha^{'}) \subseteq T_{sleep}(\alpha)$ and $T_{active}(\alpha^{'}) \supseteq T_{active}(\alpha)$.

Since $T_{sleep}(\alpha^{'}) \subseteq T_{sleep}(\alpha)$ and $|\cdot|$ is the sum of sub-time intervals in a set, $|T_{sleep}(\alpha)| \geq |T_{sleep}(\alpha^{'})|$. Similarly, $|T_{active}(\alpha)| \leq |T_{active}(\alpha^{'})|$. With the assumption that $P_{i-active} > P_{i-sleep}$, $E(\alpha) \leq E(\alpha^{'})$ by applying Eq. (14).

Since $T_{active}(\alpha) \subseteq T_{active}(\alpha^{'})$, $(T_{i-ve} \bigcap T_{active}(\alpha)) \subseteq (T_{i-ve} \bigcap T_{active}(\alpha^{'}))$. As a result, $|T_{i-ve} \bigcap T_{active}(\alpha)| \leq |T_{i-ve} \bigcap T_{active}(\alpha^{'})|$. By applying Eq. (15), $V(\alpha) \leq V(\alpha^{'})$.

The proof is complete. ■

Suppose that there are M SNs in the AAH that have a negative correlation with S_i, i.e., $LCC(S_j, S_i) < 0, j = 1, 2, \cdots M$. These M SNs are reordered as ($S_1^{'}$, $S_2^{'}$, $\cdots$, $S_M^{'}$) such that their correlation coefficients with S_i are non-decreasing, i.e. $-1 \leq LCC(S_1^{'}, S_i) \leq LCC(S_2^{'}, S_i) \cdots \leq LCC(S_M^{'}, S_i) < 0$. Consequently, the domain of α_i, [-1, 0), is divided into $M+1$ intervals (left-closed, right-open) by them as shown in Fig. 7. Let SS_{left} denote a **s**orted **s**et that

Algorithm 2: TOS

Require: D_{train}, S_i, LCG ;
D_{train}: training sensory data;
S_i: the i-th sensor node;
LCG: logical correlation graph;

```
S_neg = {S_j | LCC(S_j, S_i) < 0};
SS_left = {-1, LCC(S'_1, S_i), ··· , LCC(S'_M, S_i)};
foreach k from 0 to M
    if (V(SS_left[k]) >= V_{i-cons})    //using D_train
        α = SS_left[k];
    else
        break;
return α;
```

comprises all left endpoints of these intervals in an increasing order,

$$SS_{left} = \{-1, LCC(S_1^{'}, S_i), \cdots, LCC(S_M^{'}, S_i)\}. \tag{16}$$

Theorem 2: The ranges of $E(\alpha_i)$ and $V(\alpha_i)$ are finite, and are covered by using $\alpha_i \in SS_{left}$.

Proof: According to Eq. (11), K(α_i) is constant when α_i varies inside any interval of Fig. 7. Since $E(\alpha_i)$ and $V(\alpha_i)$ are only determined by K(α_i) according to Eqs. (12 - 15), their values also keep constant when α_i varies inside any interval. As a result, with a sub-domain of α_i that comprises sample values from all $M+1$ intervals of Fig. 7, all possible values of $E(\alpha_i)$ and $V(\alpha_i)$ are achievable. Since SS_{left} includes the left endpoints of all intervals, the ranges of $E(\alpha_i)$ and $V(\alpha_i)$ are covered by using $\alpha_i \in SS_{left}$. The proof is complete. ■

Based on the previous two theorems, a **t**hreshold **o**ptimizing **s**ub-routine (TOS) is devised to determine the threshold α_i to deactivate S_i. Four steps compose TOS: (1) It picks up all SNs in the AAH that have negative logical correlations with S_i to constitute a set S_{neg}; (2) It sorts their correlation coefficients in a non-decreasing order to generate SS_{left}; (3) It applies Eq. (15) to calculate $V(\alpha_i)$ with $\alpha_i \in SS_{left}$ sequentially until $V(\alpha_i) < V_{i-cons}$; and (4) The largest value in SS_{left} that makes $V(\alpha_i) \geq V_{i-cons}$ is the result of TOS. The pseudo-codes of TOS are presented in Table Algorithm 2.

Theorem 3: The result of TOS is an optimal solution to the problem ***P.1***.

Proof: Let α denote the result of TOS, i.e., the largest value in SS_{left} that satisfies $V(\alpha) \geq V_{i-cons}$. Assume that there exists a value β that is a better solution to ***P.1***, i.e., $E(\beta) < E(\alpha)$ and $V(\beta) \geq V_{i-cons}$. According to *Theorem 2*, there must exist a value $\beta^{'} \in SS_{left}$ such that $E(\beta) = E(\beta^{'})$ and $V(\beta) = V(\beta^{'})$. Since $E(\beta^{'}) < E(\alpha)$, according to the monotonicity proved by *Theorem 1*, $\beta^{'} > \alpha$. This is a contradiction to the hypothesis and the proof is complete. ■

The computational complexity of LCSSM in its training phase is dominated by the action of generating LCG, i.e., $O(N_{ts} * N^2)$, and the complexity in its running phase is $O(N)$. Here, N denotes the number of SNs in the AAH and N_{ts} denotes the number of time slots included in the training data. Since N is usually in a scale of tens and N_{ts} can be adjusted by applying different values of $\varDelta t$ to Eq. (1), LCSSM is customizable to different devices like a resource-limited HG and a powerful "cloud".

VI. Evaluations

Extensive evaluations have been done to validate the proposed LCSSM based on the real life-logs published by Ordonez et. al [9]. Two sets of logs "OrdonezA" and "OrdonezB", that record the daily behaviors of residents in two different AAHs, were used in the evaluations. For simplicity and clarity, only the results of "OrdonezB" are presented in this paper, since they are more typical to illustrate the characteristics of LCSSM. Needless to say, the following analyses and conclusions are also applicable to the results of "OrdonezA". In "OrdonezB", twelve SNs with different functions were deployed in a five-rooms AAH, aiming at sensing the resident's daily behaviors, e.g., leaving home, sleeping, cooking, and showering. A value of one is recorded in the log when an SN senses its VEs, while a value of zero is recorded otherwise. Sensory data were collected for a period of 21 days. Detail information on the type, deployment, and VE definition of SNs is available in [9, 25].

Five different mechanisms were compared in the following evaluations:

(1) **Duty cycling (DC):** Any conventional duty cycling mechanism such as [7, 14–16] described in Sect. II. DC provides a benchmark for the energy consumption of the remaining four sleep scheduling mechanisms, since it keeps SNs active all the time. The remaining sleep scheduling mechanisms are also assumed to have the same duty cycle ratio as DC for a fair comparison;

(2) **Energy-efficient clustering method using random update (EECRU):** A recent mechanism proposed by Wang et al. [24] that divides SNs into clusters according to the correlation of their sensory data. It activates a representative SN in turn to sense the environment, while turning off other SNs in the same cluster to save energy;

(3) **LCSSM:** The proposed sleep scheduling mechanism that activates/deactivates the sensing activity of SNs based on their logical correlations;

(4) **LCSSM-S:** A simple version of LCSSM that was presented in our previous conference paper [25]. Compared with LCSSM, it fails to automatically optimize a unique threshold to deactivate each SN, but requires a network administrator to determine a unified threshold for all SNs by experience;

(5) **Ideal sleep scheduling mechanism (ISSM):** An ideal sleep scheduling mechanism that activates SNs when their VEs occur and deactivates them when their NEs occur. Since a sleep SN usually does not know when its VEs will occur, ISSM is assumed to be able to predict the future occurrence of VEs and NEs for all SNs perfectly.

Without specifically pointing out, λ that denotes the energy consumption ratio between sleep and active modes of SNs was set to 0.5 in the following evaluations, i.e., SNs consume 1 unit of energy per second in the active mode, while consuming 0.5 unit in the sleep mode. The sensory data in first 10 days of "OrdonezB" were used to train LCSSM, LCSSM-S, and EECRU. The default length of time slots (Δt) used by LCSSM and LCSSM-S to generate LCG was 100 seconds. Regarding LCSSM-S, its threshold θ to deactivate SNs was set to -0.95 according to the preliminary experiments. Regarding LCSSM, its VHR constraint (V_{cons}), that defines the tolerable level of information loss, was set to 0.95 for all SNs.[3] Since authors do not mention how to optimize the parameters of EECRU in [24], we used their recommended ones. Finally, because the sensory data in first 10 days were used for the training phase, the previous five mechanisms were only compared based on the remaining data for fairness. Basic parameters used in the following evaluations are summarized in Table III.

TABLE III: Basic evaluation parameters.

Energy consumption ratio, λ	0.5
The length of time slot, Δt	100 secs
The constraint of VHR, V_{cons}	95%
The threshold for LCSSM-S, θ	-0.95

The five mechanisms were compared on the basis of criteria:

VE hit ratio (VHR): Defined in Sect. V-B. Higher VHR indicates a better quality of sensing;

Average energy consumption (AEC): The average amount of energy consumed by all SNs in the AAH. Since we only concern the relative performances of different mechanisms, their AECs are normalized to that of DC. Lower AEC is preferred for the energy efficiency of WSNs;

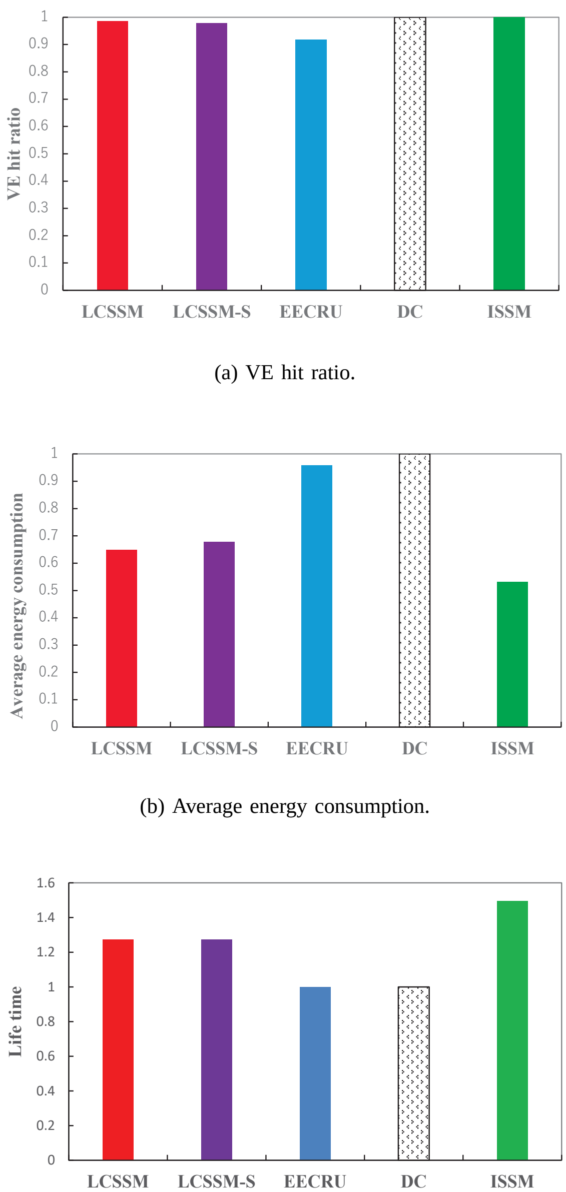
Life time (LT): Sometimes, when the first SN of WSNs in AAHs runs out of its battery, a system maintenance is required. Therefore, LT measures the length of time before the first SN runs out of its battery. Again, the LTs of all mechanisms are normalized to that of DC for the ease of comparison. Longer LT is helpful to reduce the frequency of system maintenance.

In the following evaluations, the VHRs of both DC and ISSM are always 100%, because they can sense all occurred VEs perfectly. In addition, since the AECs and LTs of five mechanisms are normalized to those of DC, DC also shows a constant value of 100% for its AEC and LT.

A. Basic Performance

Figure 8 illustrates the performances of different mechanisms with the basic parameters listed in Table III. As shown in Fig. 8, both methods based on the proposed logical correlation model ensured the quality of sensing successfully, i.e., LCSSM sensed 98.7% of occurred VEs, and LCSSM-S sensed 97.8% of them. Compared with DC, they not only reduced the AEC of WSNs (LCSSM: 65%, LCSSM-S: 67.1%), but also extended their LT (LCSSM: 127.5%, LCSSM-S: 127.5%). In addition, the energy efficiencies of LCSSM and LCSSM-S are close to that of ISSM (53.1% of AEC, 149.6% of LT). The differences were mainly due to the fact that "OrdonezB" fails to sense any behavior of its resident in about 22% of experiment time, i.e. the resident was in the home, but was out of the sensing range

[3] As shown in the problem ***P.1***, different values of V_{cons} can be used for different SNs to distinguish their tolerable levels of information loss. A unified value was used here for simplicity.

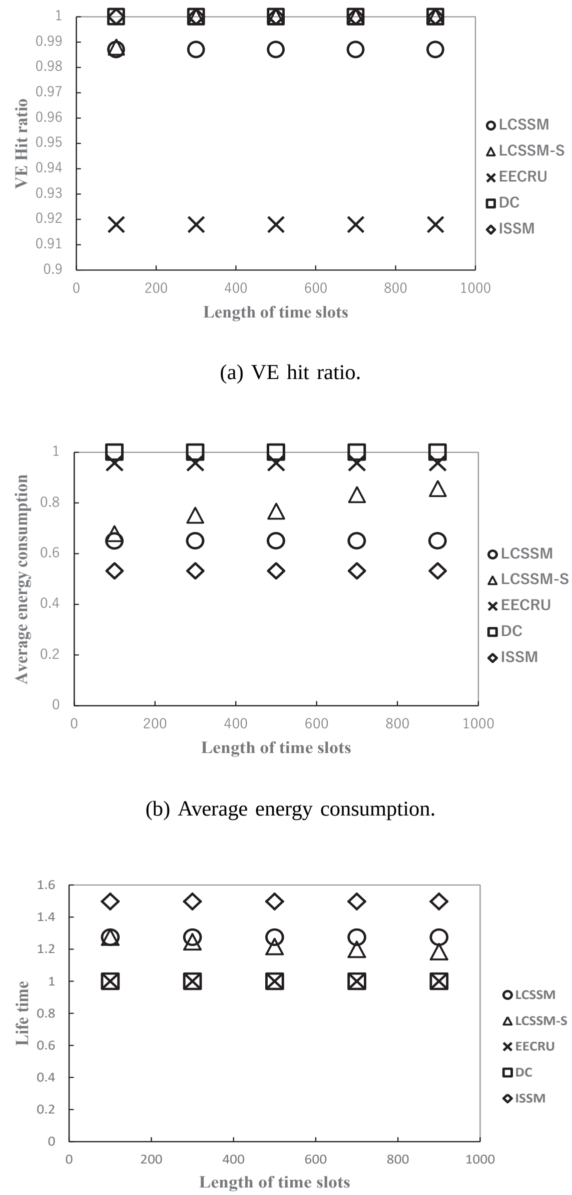


(a) VE hit ratio.

(b) Average energy consumption.

(c) Life time.

Fig. 8: Basic performances.



(a) VE hit ratio.

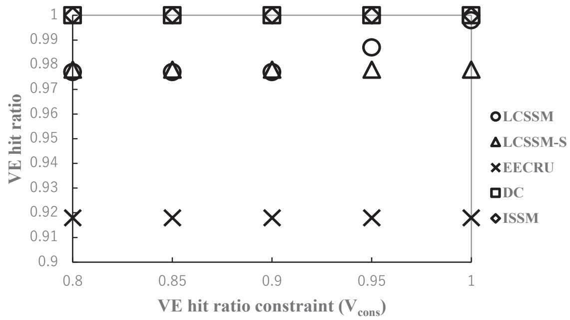
(b) Average energy consumption.

(c) Life time.

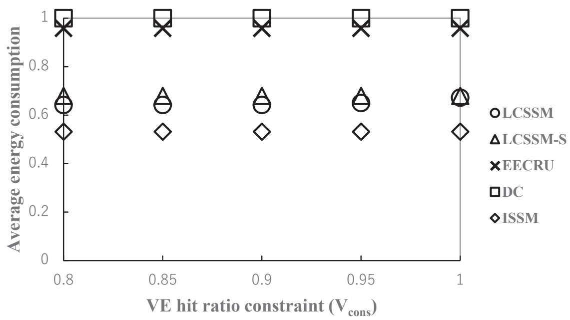
Fig. 9: Performances with different lengths of time slot (Δt) for generating LCG.

of WSNs. LCSSM and LCSSM-S had to keep all SNs active to sense the next behavior of the resident during these vacant time periods. Since ISSM is assumed to be able to predict future events perfectly, it deactivated all SNs until their next VE occurred. When excluding these vacant periods, the AECs of LCSSM and LCSSM-S are within 5% of ISSM, and the LTs of three methods are nearly the same.

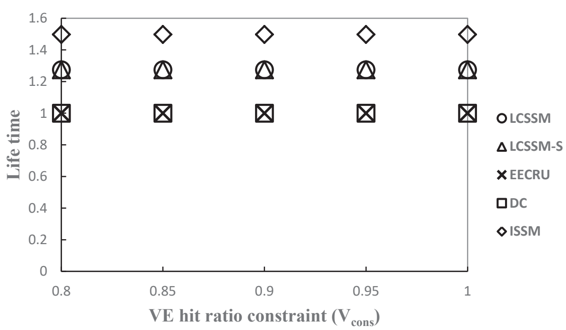
Compared with LCSSM, the performance of EECRU was not desirable. It only sensed 91.8% VEs with an AEC of 95.8%, i.e., it saved little energy. This is due to the fact that the correlation between SNs in a home continuously fluctuates according to the behaviors of its resident. For example, when the resident is watching TV in the living room, there should be a negative correlation between the SNs for TV and bed since the resident is using TV but the bed is idle. However, when the resident is using microwave for cooking, the correlation between the SNs for TV and bed becomes positive since both



(a) VE hit ratio.

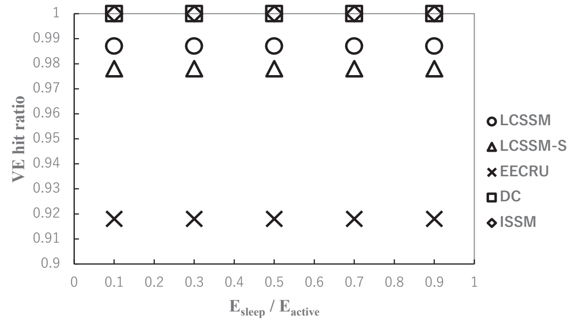


(b) Average energy consumption.

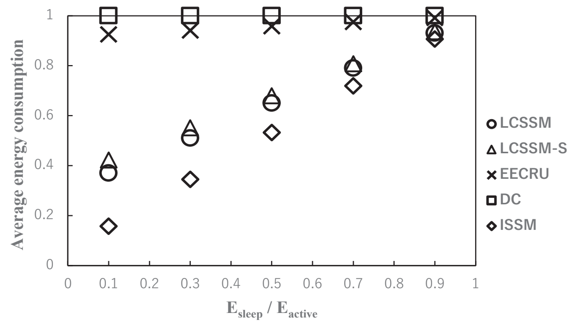


(c) Life time.

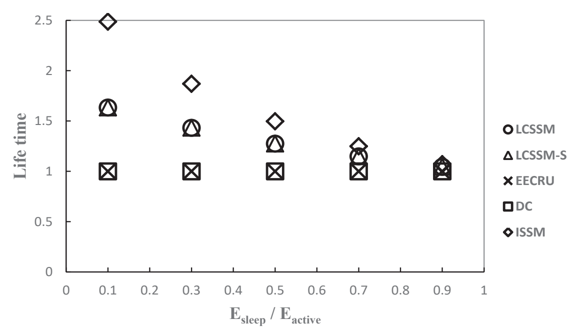
Fig. 10: Performances with different constraints of VE hit ratio (V_{cons}).



(a) VE hit ratio.



(b) Average energy consumption.



(c) Life time.

Fig. 11: Performances with different energy consumption ratios (λ) between sleep and active modes of SNs.

of them are idle. Without the ability of data preprocessing and filtering described in Sect. IV, EECRU failed to discover a steady correlation between SNs and treated these SNs as separate clusters. As a result, these SNs were always kept active since they would be the only SN in their own clusters. This also explains the reason that the life time of EECRU equals that of DC in Fig. 8(c).

B. Performance with Different Parameter Settings

It seems that LCSSM and LCSSM-S performed closely in Fig. 8. However, this is just because the threshold θ of LCSSM-S was optimized by the preliminary experiments in advance. This has been proved by Fig. 9 that depicts the performances of LCSSM and LCSSM-S with different lengths of time slots (Δt) for generating their LCGs. Although other mechanisms are not influenced by this parameter, their results have also been presented for the ease of comparison. As shown in Figs. 9(b) and (c), the energy efficiency of LCSSM-S degraded rapidly with the increase of Δt (AEC increased and LT decreased). It means that although $\theta = -0.95$ is the optimal threshold when $\Delta t = 100s$, different θ should be used for different Δt to maintain the energy efficiency of LCSSM-S. However, there is no way for LCSSM-S to optimize θ by itself. Conversely, benefitted from its ability of optimizing thresholds adaptively, LCSSM successfully maintained its energy efficiency in different settings without degrading the quality of sensing.

Figure 10 indicates the performance of LCSSM with different values of VHR constraints (V_{cons}). Since other four mechanisms are not influenced by this parameter, their results are just shown for the ease of comparison. As shown in Fig. 10(a), LCSSM successfully satisfied the constraint of V_{cons} to ensure the quality of sensing. Since the logical correlation coefficients between most SNs in “Ordonez B” were less than -0.9, an average of 97.8% (ranges from 87% to 100% for different SNs) VHR was still achieved even when V_{cons} was 85%. Consequently, the average VHR varied little when V_{cons} was less than 90%. Figures 10(b) and (c) validate that LCSSM maintained its energy efficiency with different values of V_{cons}.

Figure 11 shows the performances of five mechanisms with different values of λ. Since the VHRs of all mechanisms are not influenced by this parameter, they kept constant as shown in Fig. 11(a). A smaller λ indicates that SNs consume less energy in their sleep modes than that consumed in their active modes. Therefore, LCSSM, LCSSM-S, EECRU, and ISSM became more energy-efficient with the decrease of λ, since they can deactivate SNs to save energy, e.g., when $\lambda = 0.1$, LCSSM achieved an AEC of 37.0% and a LT of 163.4%. Again, the differences of energy consumption between LCSSM and ISSM were due to the vacant sensing periods in “OrdonezB”. ISSM deactivated SNs in vacant periods, while LCSSM kept them active. Consequently, their gap increased with the decrease of λ. As discussed in Sect. II-B, the λ of most off-the-shelf SN platforms is less than 0.67, and it easily decreases to 0.1 when duty-cycling mechanisms or energy-hungry sensors are used. Consequently, LCSSM is effective to a wide range of existing SNs. Finally, it should be noted that the efficiency of LCSSM should also increase with the advance of related electronic technologies like the energy-efficient wake-up radio of SNs [26], e.g., when the value of λ decreases to 0.01, LCSSM can achieve an AEC of 7.3%, and a LT of 292.8%.

VII. Conclusions and Discussions

This paper proposes a novel sleep scheduling mechanism named LCSSM to implement energy-efficient WSNs in ambient assisted homes (AAHs). By utilizing the particular logical correlations of an AAH to predict its usage status, LCSSM deactivates sensor nodes (SNs) to save energy when they are not expected to sense any valuable event. Compared with similar works that implement energy-efficient WSNs by using the correlation between SNs, LCSSM better fits the application scenario of AAH in which the correlation between SNs fluctuates according to different human behaviors. Extensive evaluation results have validated that the proposed LCSSM not only saves energy significantly, but also retains the quality of sensing successfully.

LCSSM can still be further discussed from several aspects:

(1) This paper assumes that AAH application is tolerable to miss part of VEs in the elder's daily life. This assumption is suitable for most ambient SNs that monitor the daily behavior of elders who suffer from chronic disease, but may not work for life-critical SNs like those monitor some acute heart diseases. In fact, LCSSM can also be used for life-critical SNs by softening the definitions of their active and sleep modes. Instead of deactivating life-critical SNs completely, we can define a lower but safe sensing frequency for the sleep mode and use this mode when the incidence of vital disease is low. Conversely, a higher sensing frequency can be used in the active mode when the incidence of vital disease is high. By switching between active and sleep modes, LCSSM can safely improve the energy-efficiency of life-critical SNs.

(2) The concept of AAH can be extended to other environments like hospitals and nursing homes, where several elders may live together. It is clear that there are some kinds of logical correlation between SNs under these situations, e.g., when all elders are sleeping at night, appliances are not likely to be used; and when an elder is sleeping in bed, her/his roommates prefer not to watch TV to avoid making noise. It is interesting to refine LCSSM and evaluate its performance in these scenarios. However, we think the value of AAH deteriorates in these scenarios since elders can take care of each other conveniently.

(3) When the life-style of an elder changes as time passes, the previous logical correlations between SNs may become out of date. One way to overcome this issue is to update the logical correlations between SNs every certain period of time. According to the frequency of update, there is a tradeoff between the adaptation of LCSSM and the computational overhead. It is also interesting to design an on-line mechanism that can update the logical correlations between SNs incrementally.

(4) Since the concept of logical correlation between SNs is universal, we are expecting its utilization in other applications like WSNs for car parking and surveillance. For example, there may exist certain correlation between the use of different parking lots in a city, i.e., when parking lots in the central business district are full in the work time, parking lots in the uptown are usually empty. It seems interesting to use this kind of intrinsic correlations to schedule their WSNs. These attempts are also instrumental to explore the full potential of this concept, e.g., how to take advantage of the positive correlations between SNs to schedule WSNs.

References

[1] U. DeSA, “World population prospects: the 2012 revision,” *Population Division of the Department of Economic and Social Affairs of the United Nations Secretariat, New York*, 2013.
[2] J. Lloret, A. Canovas, S. Sendra, and L. Parra, “A smart communication architecture for ambient assisted living,” *Communications Magazine, IEEE*, vol. 53, no. 1, pp. 26–33, 2015.
[3] Carbinet Office, Goverment of Japan, “Annual report on the aging society: 2014,” Tokyo, Japan.

[4] J. Gubbi, R. Buyya, S. Marusic, and M. Palaniswami, "Internet of things (iot): A vision, architectural elements, and future directions," *Future Generation Computer Systems*, vol. 29, no. 7, pp. 1645–1660, 2013.
[5] A. Zanella, N. Bui, A. Castellani, L. Vangelista, and M. Zorzi, "Internet of things for smart cities," *IEEE Internet of Things Journal*, vol. 1, no. 1, pp. 22–32, 2014.
[6] H. Lindgren and C. Yan, "Acktus: A platform for developing personalized support systems in the health domain," in *Proceedings of the 5th International Conference on Digital Health 2015*, ser. DH '15. New York, NY, USA: ACM, 2015, pp. 135–142.
[7] H. Pensas, M. Valtonen, and J. Vanhala, "Wireless sensor networks energy optimization using user location information in smart homes," in *Broadband and Wireless Computing, Communication and Applications (BWCCA), 2011 International Conference on*, 2011, pp. 351–356.
[8] A. Wood, J. A. Stankovic, G. Virone, L. Selavo, Z. He, Q. Cao, T. Doan, Y. Wu, L. Fang, and R. Stoleru, "Context-aware wireless sensor networks for assisted living and residential monitoring," *Network, IEEE*, vol. 22, no. 4, pp. 26–33, 2008.
[9] F. J. Ordónez, P. de Toledo, and A. Sanchis, "Activity recognition using hybrid generative/discriminative models on home environments using binary sensors," *Sensors*, vol. 13, no. 5, pp. 5460–5477, 2013.
[10] G. Yang, L. Xie, M. Mäntysalo, X. Zhou, Z. Pang, L. Da Xu, S. Kao-Walter, Q. Chen, and L.-R. Zheng, "A health-iot platform based on the integration of intelligent packaging, unobtrusive bio-sensor, and intelligent medicine box," *IEEE transactions on industrial informatics*, vol. 10, no. 4, pp. 2180–2191, 2014.
[11] F. J. Ordóñez, P. de Toledo, and A. Sanchis, "Sensor-based bayesian detection of anomalous living patterns in a home setting," *Personal and Ubiquitous Computing*, vol. 19, no. 2, pp. 259–270, 2015.
[12] R. C. Carrano, D. Passos, L. Magalhaes, and C. V. Albuquerque, "Survey and taxonomy of duty cycling mechanisms in wireless sensor networks," *Communications Surveys & Tutorials, IEEE*, vol. 16, no. 1, pp. 181–194, 2014.
[13] A. Reinberg, *Les rythmes biologiques mode d'emploi*. Flammarion, 1994.
[14] J. Polastre, J. Hill, and D. Culler, "Versatile low power media access for wireless sensor networks," in *Proceedings of the 2nd international conference on Embedded networked sensor systems*. ACM, 2004, pp. 95–107.
[15] W. Ye, J. Heidemann, and D. Estrin, "An energy-efficient mac protocol for wireless sensor networks," in *INFOCOM 2002. Twenty-First Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings. IEEE*, vol. 3, 2002, pp. 1567–1576 vol.3.
[16] H. Le, J. Van Eck, and M. Takizawa, "An efficient hybrid medium access control technique for digital ecosystems," *Industrial Electronics, IEEE Transactions on*, vol. 60, no. 3, pp. 1070–1076, 2013.
[17] V. Raghunathan, S. Ganeriwal, and M. Srivastava, "Emerging techniques for long lived wireless sensor networks," *Communications Magazine, IEEE*, vol. 44, no. 4, pp. 108–114, 2006.
[18] C. Alippi, G. Anastasi, M. Di Francesco, and M. Roveri, "Energy management in wireless sensor networks with energy-hungry sensors," *Instrumentation & Measurement Magazine, IEEE*, vol. 12, no. 2, pp. 16–23, 2009.
[19] V. Jelicic, M. Magno, D. Brunelli, G. Paci, and L. Benini, "Context-adaptive multimodal wireless sensor network for energy-efficient gas monitoring," *Sensors Journal, IEEE*, vol. 13, no. 1, pp. 328–338, 2013.
[20] I. F. Akyildiz, M. C. Vuran, and O. B. Akan, "On exploiting spatial and temporal correlation in wireless sensor networks," in *Proceedings of WiOpt*, vol. 4, 2004, pp. 71–80.
[21] C. Liu, K. Wu, and J. Pei, "An energy-efficient data collection framework for wireless sensor networks by exploiting spatiotemporal correlation," *IEEE Transactions on Parallel and Distributed Systems*, vol. 18, no. 7, pp. 1010–1023, 2007.
[22] L. A. Villas, A. Boukerche, H. A. De Oliveira, R. B. De Araujo, and A. A. Loureiro, "A spatial correlation aware algorithm to perform efficient data collection in wireless sensor networks," *Ad Hoc Networks*, vol. 12, pp. 69–85, 2014.
[23] E. Karasabun, I. Korpeoglu, and C. Aykanat, "Active node determination for correlated data gathering in wireless sensor networks," *Computer Networks*, vol. 57, no. 5, pp. 1124–1138, 2013.
[24] F. Wang, S. Wu, K. Wang, and X. Hu, "Energy-efficient clustering using correlation and random update based on data change rate for wireless sensor networks," *IEEE Sensors Journal*, vol. 16, no. 13, pp. 5471–5480, 2016.
[25] W. Liu, Y. Shoji, and R. Shinkuma, "Logical correlation-based sleep scheduling for energy-efficient WSNs in smart homes," in *PIMRC 2015. 26th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications. Proceedings. IEEE*, 2015, pp. 2176–2181.
[26] J. Oller, I. Demirkol, J. Casademont, J. Paradells, G. U. Gamm, and L. Reindl, "Has time come to switch from duty-cycled mac protocols to wake-up radio for wireless sensor networks?" *IEEE/ACM Transactions on Networking*, vol. 24, no. 2, pp. 674–687, 2016.